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Benchmarking of hydroelectric stochastic risk management models using financial indicators

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Abstract

The objective of this paper is to present the operating and hedging analysis of a hydroelectric system in a non-hydro dominated market using a specifically-developed tool for operating and contracting decisions. Hydropower companies are likely to face stochastic inflows, spot prices, and forward prices, during their operation. The objective of the tool is to maximize expected revenues from spot and forward market trading, considering suitable indicators of the company risk aversion. We benchmark the implemented risk indicator of required Minimum Revenues in the optimization tool using financial risk indicators, such as Value at Risk, Conditional Value at Risk, and the Risk Premium of a Utility function. This portfolio management problem, which includes physical and financial assets, is formulated as a stochastic revenue maximization problem under a specified risk aversion constraint. The company risk aversion is apprehended by penalizing reservoir operation and derivative instruments contracting decisions policies that lead to financial performances that are violating the required Minimum Revenues at the end of a predefined profit period. A hybrid Stochastic Dynamic Programming (SDP) / Stochastic Dual Dynamic Programming (SDDP) formulation is adopted to solve this large-scale optimization problem.

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1. INTRODUCTION

Electricity markets in developed countries have evolved from a regulated to a somewhat liberalized competitive environment switching from a monopoly, where electricity prices were guaranteed by the government, to a liberalized and competitive environment, led to restructuring and deregulation. Given the non-storability characteristics of electricity and the inelasticity of demand, markets are functioning under very complex mechanisms [1]. Newly constituted markets are either monopolies and oligopolies where market participants have market power and are price setters, or fully competitive ones were players are considered price takers. The unbundling of the electricity sector into transmission, generation, and distribution, along with the establishment of various physical and financial markets has shifted the interest of power producers from cost minimization (CM) to revenue maximization (RM).

The markets that exist in Europe are both of financial and of physical natures. Financial markets are the futures contracts market (or Contracts For Differences) and the options on futures contracts. In the financial markets, at delivery, the contracts are settled in cash. The forwards contracts, the options on forwards contracts, the spot, the intra-day, and the balancing, are financial markets with physical delivery at maturity. The forwards contracts are traded Over The Counter (OTC). Figure 1 describes the various types of European power markets.

Real time markets
- Balancing market
- Intra-day market

Day + 1 markets
- Spot auction
- D+1 OTC market

Financial Markets
- Futures contracts
- Options on futures

Forwards Markets
- Forwards contracts
- Options on forwards

Fig.1: European power market types.

The ultimate goal of the utilities is to maximize the value of their asset portfolio under well-defined risk constraints that represent their risk aversion, using the available physical and financial electricity markets. A typical portfolio of a utility consists of generation, customer load profiles, and physical and financial derivatives. Electricity markets can be used either for risk transferring and hedging purposes or for risk seeking and speculative purposes. These two opposite cases define the risk aversion or risk proneness attitude of a company. Given the ownership structure of these companies, usually a very stable growth of gross margin is expected. For this reason, most of the utilities seek to maximize their revenues, while having a controlled exposure to financial risk, using electricity markets for risk mitigation.

The electric power industry is following closely the evolution of the banking industry as far as deregulation and operations are concerned. A series of risk management practices have thus been borrowed and adapted accordingly. Examples of these risk management practices are the use of financial risk indicators such as Value at Risk (VaR) [9], Conditional Value at Risk (CVaR) [10], and the Risk Premium of a Utility Function (UF) [11].

In the case of companies with a hydroelectric-based portfolio, risk management practices are coupled with complex optimization algorithms to consider the main stochastic sources of the problem (inflows and prices) along with all constraints of technical and financial natures. The financial constraint mostly used in these cases is the "Minimum Revenue" (Rmin) risk indicator, which has been implemented as a risk aversion constraint in the stochastic hydroelectric middle term optimization tools.

One interesting and important issue is then the performance of the Rmin criteria when compared to the standard financial indicators, such as CVaR, VaR, and UF. This is the main focus of the work presented in this paper.

Based on the existing state-of-the-art modelling of optimization for hydro-asset revenue maximization, the work presented here derives from an in-depth analysis of a hydro-based portfolio in the European market, owned by a major electricity player. Using the above mentioned financial risk indicators of VaR, CVaR, and the Risk Premium of the UF, we analyze the performance of the Rmin constraint that is implemented into our model. In this paper, we will consider a single price area and using hydro production.

This paper is organized as follows: in section II, III and IV we describe the methodology and the state of the art of the underlying theory. Section V describes the system that will be analyzed and section VI presents the results of the analysis of the system. In section VII we will draw a series of conclusion on the above-mentioned issues. Finally, in section VIII we present possible further developments.

2. BIDDING STRATEGIES FOR HYDRO AGENTS

One of the key components in liberalized power sectors for hydro-based companies is the medium-term electricity market, where strategic reservoir operation and financial hedging occur. Using the spot market and the expected spot market price, risk and sensitivity analyses are conducted. The existence of a competitive electricity spot market raises complex optimization challenges for the different players.

There are two types of players: the price takers and the price makers. In this paper, we will refer only to price takers. A price-taker has not the power to alter the market price with its bids. It is widely accepted that its optimal bidding strategy is to bid the plant short-run variable operating cost, as shown in [2]. In the case of thermal plants, this strategy is straightforwardly applicable, because the variable costs are (essentially) a function of fuel costs. In the case of hydro plants, however, the problem is more complex. The reason is that hydro reservoirs allow the bidder to postpone energy generation until future prices are expected to be higher than the current price. As a consequence, the plant variable cost is actually an opportunity cost, which depends on joint future scenarios of inflows and prices. The calculation of opportunity costs for hydro systems is a complex stochastic optimization problem, which is usually solved by Stochastic Dynamic Programming (SDP) techniques.

For the traditional least-cost (LC) scheduling of hydrothermal systems, the stochastic dual dynamic programming (SDDP) algorithm [3] has been extensively used. In the Least Cost (LC) environment [4], all generators are centrally scheduled by a system operator, having the objective of minimizing expected operation costs along the study period. The stochastic parameters are the inflows to each hydro reservoir, modelled as a variable lag auto-regressive AR(P) model. The LC scheduling is formulated as a SDP model, where the state variables are the reservoir storage levels and the observed inflows in the previous months. The SDDP scheme approximates the future cost function of the SDP recursion by a piecewise linear function. The linear pieces of this function are obtained from the dual solutions of a one-stage optimization problem at each stage. In this case we do not need to use discrete states , thus avoiding the combinatorial "explosion" with the increasing number of states – the so-called "curse of dimensionality" of dynamic programming. An iterative scheme, similar to the multi-stage Benders decomposition [5], improves the piecewise approximation and provides lower and upper bounds to the optimal problem solution. The SDDP algorithm has been applied to the scheduling of large-scale power systems in more than thirty countries, including detailed modeling of system components and transmission networks ([6]).

On liberalized electricity markets, the objective of a hydroelectric generation company is to develop operation strategies that maximize its revenues, from the spot market trading, taking into account the use of the hydro system storage capabilities to schedule its energy production over time. In this case, it is necessary to build a "future revenue function" - or future benefit function (FBF) - for the company's generation portfolio, similar in concept to the future cost function of the LC scheduling; which represents the expected revenue of the generation company from a given stage until the end of the considered period. The objective of the company is then to maximize the sum of its immediate and future expected revenues, which are both concave as shown in Figure 2.

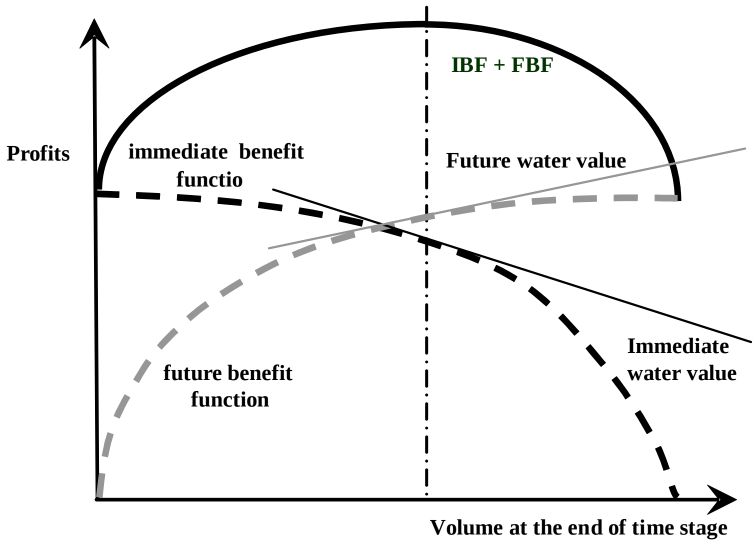

Fig. 2: Immediate benefit function (IBF) and future benefit function (FBF).

3. A MODEL FOR SIMULTANEOUS PHYSICAL/FINANCIAL OPTIMIZATION

3.1 Operating decisions (physical) optimization

Assuming the power generation company is a price-taker agent, spot market prices become input parameters to hydro scheduling models. Inflow and prices are auto-correlated, by carrying information about the likely outcomes in the future (each one through an independent process). Therefore we have two main stochastic variables (prices and inflows), which must be treated as state variables in Dynamic Programming models. This makes difficult to apply directly the SDDP algorithm because the future benefit function is no longer concave in the dimensions of all state variables – it becomes convex in objective function coefficients (prices) and concave in the constraints coefficients (inflows). Thus, the future benefit function can no longer be supported by the linear cuts. This was first discussed in [7] where an algorithm was introduced in which there was no cut sharing across price states, i.e., the future cost function was built for each price state at each stage. This approach was later used in power generation scheduling models under price uncertainty in Norway [8]. The problem is solved by a discrete/continuous hybrid SDP/SDDP scheme, where the spot price states are represented by discrete intervals (price clusters), while the effect of inflow uncertainties on future operating decisions are represented by continuous piecewise linear approximations. Price clustering can be realized using various techniques such as Equiprobable and K-means clustering. The methodology for the Equiprobable method is the following: Given N different price scenarios, each cluster $i \in K$ will have the same number of elements $n_i = N/K$ (unless the number of scenarios is not a multiple of K, in which case the lower clusters will have one more element). This way, all clusters will have the same estimated probability of occurrence, therefore Equiprobable. The K-means method is based on the identification of a representative subgroup of the sample, in a way that minimizes the Euclidean distance between each cluster centre and the points in the sample that it represents.

3.2 Contracting decisions (financial) optimization

On the liberalized markets, in presence of a spot market and derivatives markets, a company has a greater flexibility for optimizing both the operating and contracting decisions according to its risk aversion (in markets where no derivative markets exist, risk aversion can be taken into account through reservoir operation and standard load contracts). In the Revenue Maximization (RM) under risk aversion constraints problem, power producers can sell their energy production in the spot market, and they can also trade in the derivative markets having as an objective to maximize revenues subject to their risk aversion.

3.3 A model for simultaneous optimization

We have developed a tool based on the same principles used in the work pioneered by [7,8], the objective of which is to support the operating and financial decisions that maximize the company total revenues, taking into account stochastic prices, inflows, and risk constraints. It is not the objective of this paper to describe the tool in detail; instead, the focus here is only on the benchmarking.

In our tool, we consider forward contracts of different types and liquidities. The objective being in this context to maximize the sum of expected revenues from trading in the spot and forwards minus the penalty for not fulfilling the revenue constraints over the defined profit period. The required Rmin constraint is introduced as a penalty in the objective function in case the constraint is violated, i.e. the required Rmin is not achieved at the end of each profit period. The penalization in the objective function is calibrated using a penalty coefficient. The proposed solution methodology is an extension of the SDDP algorithm. The RM scheduling is also formulated as a SDP recursion, where the spot price is modelled as a Markov process, and the state variables, in addition to storage levels and past inflows, now include spot prices, forward prices (equal to the expected spot price), forward contract energy, forward contract revenues and accumulated revenues per profit period.

4. RISK BENCHMARKING

The analysis method used in this work is based on a series of indicators that describe the result of the reservoir operation and trading decisions on the spot and forwards market. These indicators are of physical and financial natures. The indicators of physical nature are the net delivered energy in the spot, the net delivered energy in the forward market, the energy bought in the spot and the “hedging cost”. The “hedging cost” is calculated as the difference between the forward revenues and spot purchases in the day of delivery multiplied by the percentage difference between the buy and sell price (a constant percentage difference between buy and sell prices is assumed). The financial risk indicators are VaR and CVaR for various probability levels, and the Risk Premiums of two piecewise Utility Functions representing different risk aversions. In the case study analysis we look at benchmarking the efficiency of the Rmin constraint already implemented in the model through the use of the above-mentioned financial risk indicators. From this analysis we can conclude whether the Rmin indicators can be used as a proxy for the VaR, CVaR and/or Utility Function risk aversion constraints.

5. DESCRIPTION OF THE CASE STUDY SYSTEM

The hydro system analyzed in this work is located in France, in two distinct hydrologic regions: Region A and Region B. Region A has the inflows of a mountainous type and Region B of a rural type. It consists of 8 river basins (hydro cascades): 6 in Region A and 2 in Region B. The total installed capacity of the 35 hydropower plants is 807MW. There are 15 reservoirs with a storage capacity of 135 hm^3. The system has a hydrological cycle of one year (staring in May and finishing in April) and, due to its storage capacity, there is limited potential for energy transport within the year.

The system production is exposed to the spot electricity and the green market. The green market in France is accessible only by small hydro-electric stations (under 12 MW) and the Type A tariff (Jan 2005 data) guarantees a constant price of 42.4 EUR/MWh.

6. RESULTS

6.1 Simulations context and description

Within the framework of a project conducted for a European hydropower company, we have analyzed the performance of the system operation under the requirement of maximizing the expected revenues while taking into consideration corporate risk constraints. The main points of the analysis are: production risk, revenue risk, medium-term planning benefit, and benchmarking of the risk aversion decisions using the aforementioned physical and financial indicators.

The study was conducted using 100 inflows and 100 price scenarios randomly combined. As the French market has a small share of hydro power (approx. 14%); we assume no correlation between inflow and price scenarios. Inflow scenarios are generated using an autoregressive model of order *p* (AR(P)), which parameters have been estimated using historical inflow data. The electricity spot price scenarios were generated using a company in-house model. This model generated hourly spot price scenarios that were aggregated into weekly blocks. Prices are finally regrouped in cluster in the model using the method of K-means as described in the methodology.

A first series of comparative runs was made between the cases of simultaneous and two-stage decisions for reservoir operation and contracting decisions. Due to the system’s limited potential of energy transport within the year and the fact that we are considering a one-year profit period, the results showed no difference. In addition, depending on the company structure and system operation, decisions can be made in a different company department than contracting decisions. Furthermore, in terms of calculation time, the full simultaneous optimization takes 11.5 hours, compared to the two-stage optimization that takes 2 hours. The runs where made with a 2.0GHz Centrino CPU with 1GB of RAM, which showed to be 1.5 times faster than the Pentium IV 3.2GHz HT with the same amount of RAM. The system is optimized for a three year horizon and weekly time steps, and we analyzed the results of the middle year. For the contracts optimization we considered weekly and monthly forward contracts. The liquidity considered is 4 weeks ahead and 3 additional months beyond the weekly contracts. We considered one profit period during the second year where revenues have to be greater than a given Rmin level.

6.2 System Operation Optimization

Table I displays the statistical analysis of the inflow and price scenarios that were used for the system’s optimization. Both statistical indicators refer to the 100 Scenarios (inflow and price) of annual data.

Table I – Inflow and Prices Statistical Analysis.

	Inflow Energy (GWh)	Spot Prices (Eur/MWh)
Average	835.13	31.46
Min	519.92	21.72
Max	1180.73	44.02
StdDev	106.4	4.81
CV	13%	15%

Table II displays the statistical analysis of the annual energy and revenues generated for the whole system.

Table II – System Optimization.

	Generation GWh)	Revenues (kEUR)
Average	1'819	65'542
Min	1'152	45'891
Max	2'148	98'359
StdDev	181	12'088
CV	10%	18%

Figure 3 displays the cumulative distribution of the annual generation for the entire system (total). As we can see, depending on annual hydrologic conditions, the total production can vary from 1152 GWh (dry year) to 2148 GWh (wet year). In addition, the generation that is sold to the green market shows a minor variation for the different inflow scenarios. This characteristic is inherent to the systems topology and inflows.

Figure 3 also displays the cumulative distribution of the total annual revenue (total). We can see that from one year to the next, revenues can double, from 45 M€ to 98 M€. Here, low revenues correspond to the conjunction of relatively low prices and low inflows, while high revenues occur essentially with higher inflow scenarios and price scenarios characterized by price spikes. This occurs because we have uncorrelated prices and inflows, if a negative correlation between them had been considered the opposite behavior would be expected where low prices would occur with high inflows.

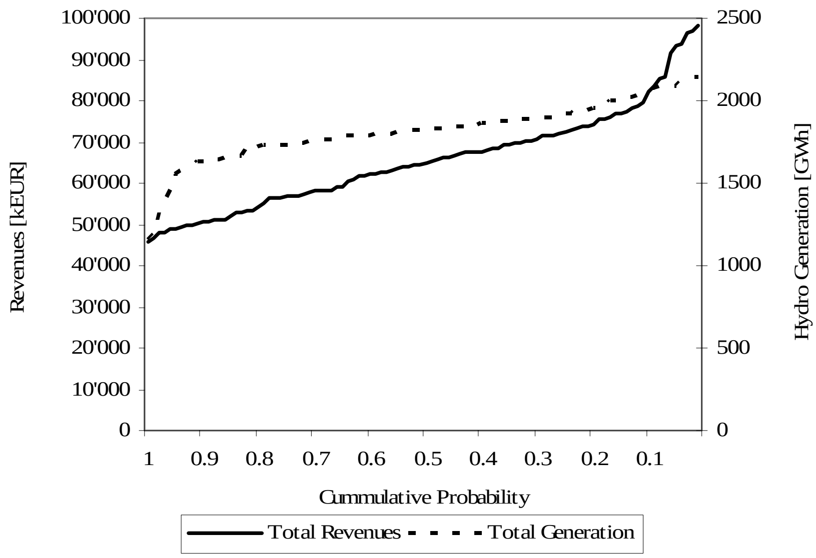

Fig. 3: Cumulative probability of the scenarios of annual revenues.

Figure 4 displays the average weekly generation in relation to the average weekly prices. Although an average scenario representation smoothes the instantaneous extreme variations, we can see however that the system has greatly concentrated the highest level generation during the period of lower prices. As we can observe in the Figure 5 this occurs because of the high inflow energy during this period combined with the system low storage capacity. This increase of the inflow level is mainly due to the ice melting from the mountains in the «good season”.

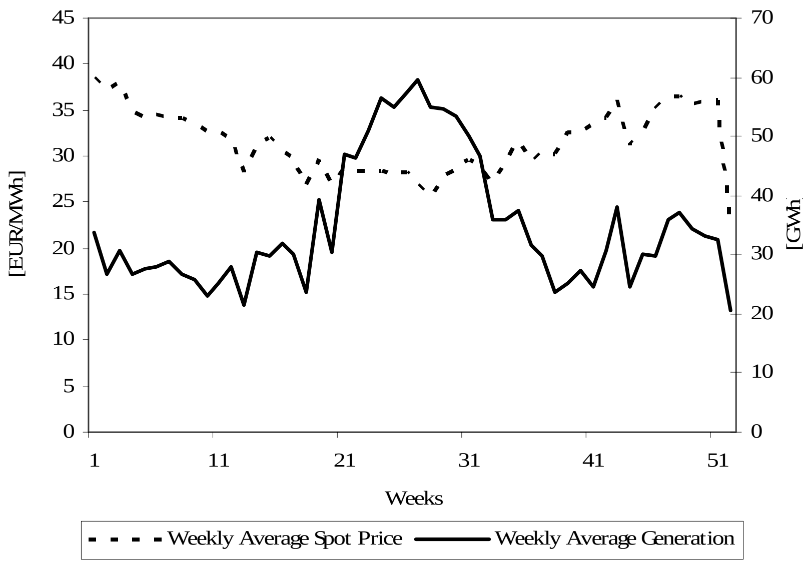

Fig 4: Weekly average generation in relation to the weekly average spot price.

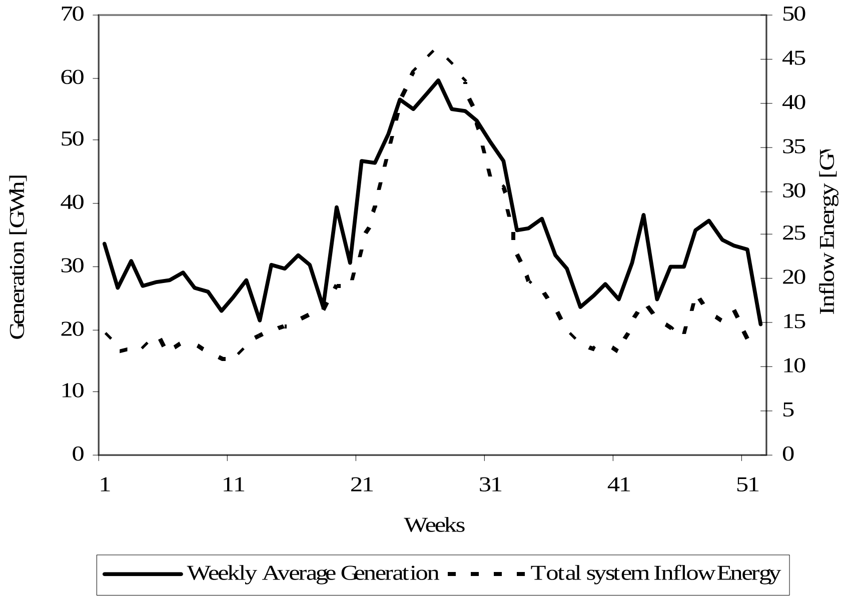

Fig.5: Weekly average generation in relation to the weekly inflow energy.

6.3 Risk decomposition

One important risk approach in risk management practices for hydro portfolios is the decomposition of the total risk into price risk and inflow risk. A series of reservoir constrained simulations were made in order to decompose and quantify the price risk and the inflow risk. In a reservoir operation, both the price and inflow state variables drive the operating decisions. Hence, the share of each one in the total risk must be calculated by isolating it rather than considering it independently of the other. These simulations consist in exposing the system operation to the inflow risk by restraining the reservoir operation optimization by assuming a storage volume of zero. This way, we eliminate the incentive of prices for the reservoir operation. These generation scenarios results, each one multiplied by the average price scenario value, yield the revenue scenarios levels related only to the inflow state variable. In order to calculate the equivalent revenue scenarios that are related to the price state variable we multiply the average scenario generation of the above-mentioned simulations with each of the price scenarios values.

The decomposition of the risk then indicates the part of the risk, related to price variation, which can be hedged using financial instruments. The part of the risk that is related to inflow variations is mitigated through the energy transport within the year. In our system, given the limited potential of energy transport, such transports are restrained to periods varying from one week to one month. The risk decomposition results are displayed in Table III.

Table III – System's Risk Decomposition.

	St-Dev (kEUR)
Total	12'088
Price Risk	7'459
Inlfow Risk	6'806

In Table IV we give the results from another series of specially constrained simulations that were used to quantify the differences between the benefits of a middle term and a short term only optimization, which tends to be more "myopic" with respect to the future behavior of the system. Although in this system a large amount of benefits derives from the short term optimization, due to its topology, we can see that in average the benefit of middle term optimization is 9%.

Table IV – Optimization Tool Benefit.

		MT Optim.	ST Optim.	Differences
Average	[kEUR]	65'542	59'643	9.0%
Min	[kEUR]	45'891	40'843	11.0%
Max	[kEUR]	98'359	90'982	7.5%

6.4 Contracting Decisions Optimization

As mentioned in the simulation context description, simulations were made first for the reservoir operating decisions optimization. In a second stage, using the same tool with bounded reservoir operating decisions we optimized the contracting decisions. By bounding reservoir decisions, we use the already calculated operating policy to calculate the contracting decision policy. The initial contract portfolio did not contain any existing forward or client load profile contracts. We have focused our study on the use of forwards contracts as hedging instruments. We have assumed inelastic spot and forward prices considering the small amounts traded relative to the whole market size. As mentioned above, the objective of the analysis was to benchmark the implemented risk indicator of Rmin using the indicators of VaR, CVaR, and the Risk Premium indicator of a UF. In our analysis, we have chosen to use probability levels of VaR and CVaR corresponding to the Rmin levels that were used as risk aversion constraints. The break points of the two piecewise linear UF were chosen accordingly. We have selected the Absolute Risk Aversion Coefficients (ARAC) of the two UF so as to represent two levels of risk aversion.

The purpose is to draw conclusions on the use of the Rmin indicator as a proxy for the above-mentioned financial risk indicators. For that we have made a series of simulations using five levels of Rmin that have to be guaranteed during the profit period of one year (middle year); these correspond to operational levels of the company. Such operational levels are Short Run Marginal Cost, Operation and Maintenance Cost, Cash flow requirements from banks and rating companies, dividend payments to shareholders. We have chosen as levels of Rmin the lowest 5%, 10%, 20%, 30% and 40% of the accumulated annual revenues during the one-year profit period among the 100 revenue scenarios. As mentioned in the methodology section, the Rmin indicator is implemented through penalization (using a violation decision variable calibrated by a penalty coefficient) of the revenue scenarios that give results under the required Rmin. This penalization is applied to the objective function by subtracting the penalty from the revenues. Hence, the sum of differences between the scenarios results that are under Rmin and the required Rmin is minimized in order to decrease the penalty at the most possible. Therefore, a direct measure of the risk aversion using the Rmin constraint is the sum of differences of the revenue scenarios that are under the required Rmin for each simulation. We have made a series of simulations in order to identify the penalty coefficient leading to the least possible sum of differences.

Table V displays the five levels of Rmin along with the sum of differences and the cost of hedging. We can observe that for the revenue scenarios with Rmin higher than 10% of Rmax the required Rmin cannot be fully achieved (it remains greater than zero). This is related to the available generation capacity and the length of liquidity of the forwards contracts used. In addition, we can see that the cost of hedging for the improvement of the lower 40% of the revenue scenarios is the double than the one of 30%. This is due to the increased contracting activity and then the purchase from the spot for the scenarios for which there is not enough energy generated to satisfy the energy contracted in forwards.

Table V – Rmin Levels.

Rmin (kEUR)	Rmin (%) of Rmax	Difference from Rmin Sum (kEUR)	Cost of hedging Average (kEUR)
48'917	**5%**	0	265
50'002	**10%**	0	341
53'388	**20%**	192	421
57'742	**30%**	1'765	829
61'922	**40%**	5'113	1'624

Related to the Table V, Table VI shows the breakdown between the Spot market and Forwards market delivery. We can see that the largest the number of revenue scenarios that has to be improved (higher Rmin required), the lower the spot market delivery and the higher the forwards market delivery. In the case of 40%, we can observe that on average there is more forward contract delivery than spot delivery. This is explained by the combination of scenarios with relatively high forward prices and low inflows. In these scenarios, the system is required to purchase in average more energy than it sells on the spot market in order to cover the forward contracts energy delivery.

Table VI – Rmin Levels.

Rmin (kEUR)	Rmin (%) of Rmax	Spot delivery Average (GWh)	Forward delivery Average (GWh)
0	**0%**	1'363	0
48'917	**5%**	893	305
50'002	**10%**	805	345
53'388	**20%**	853	251
57'742	**30%**	305	533
61'922	**40%**	-463	846

Table VII displays the probability level of VaR and CVaR of the required Rmin on the revenue scenario distributions for the five risk aversion simulations. We can observe that the VaR corresponding to the lower 5% and 10% are improved to 100% (Rmin guaranteed for the totality of the scenarios). For the higher levels of revenue scenarios, although the improvements are important, they do not reach 100%. The improvement of CVaR, for the cases where CVaR is greater than zero, increases more steadily for the different Rmin levels.

Table VII – Rmin Levels.

Rmin (kEUR)	Rmin (%) of Rmax	VaR of Rmin (%)	CVaR of Rmin (%)
48'917	**5%**	100	0
50'002	**10%**	100	0
53'388	**20%**	98	53'172
57'742	**30%**	94	57'240
61'922	**40%**	84	61'591

In the Tables VIII and IX we present the analysis of the results of the Rmin benchmarking for five levels of VaR and CVaR. These levels of VaR and CVaR are chosen accordingly to the levels of Rmin. Although the VaR value is not improving significantly for the higher required Rmin, the CVaR continues improving by the same amount compared to the initial non risk aversion revenue result. This is related to the technique of implementation of Rmin constraint in the tool as explained below. As mentioned in the methodology section, in order for the algorithm to satisfy the Rmin constraint, the sum of differences of the revenues below the Rmin level is penalized. CVaR, in this case, is the average of the revenues below the Rmin, which is linearly related to the sum of differences of these revenues. We can deduct from this observation that Rmin could be used efficiently as a proxy for the CVaR. However, given the discreet nature of VaR, the expression of risk aversion through the Rmin does not have the same efficiency when considering VaR.

Table VIII – VaR Levels.

Rmin (kEUR)	Rmin (%) of Rmax	VaR 95% (kEUR)	VaR 90% (kEUR)	VaR 80% (kEUR)	VaR 70% (kEUR)	VaR 60% (kEUR)
0	**0%**	48'917	50'002	53'388	57'742	61'922
48'917	**5%**	51'250				
50'002	**10%**	52'988	53'542			
53'388	**20%**	53'390	53'522	54'970		
57'742	**30%**	57'343	57'697	58'096	60'278	
61'922	**40%**	61'617	61'755	62'053	62'203	62'655

Table IX – CVaR Levels.

Rmin (kEUR)	Rmin (%) of Rmax	CVaR 95% (kEUR)	CVaR 90% (kEUR)	CVaR 80% (kEUR)	CVaR 70% (kEUR)	CVaR 60% (kEUR)
		47'533	48'581	50'261	52'332	54'141
48'917	**5%**	50'155				
50'002	**10%**	51'606	52'453			
53'388	**20%**	53'261	53'370	53'732		
57'742	**30%**	57'192	57'390	57'630	58'223	
61'922	**40%**	61'159	61'436	61'670	61'823	61'981

6.5 Utility Functions

The Utility Functions used for the analysis take into account two different levels of risk aversion. UF 1 corresponds to a higher risk aversion than UF 2. The different risk aversions are expressed through the choice of the Absolute Risk Aversion Coefficients (ARAC), which are the differences between the slopes of the linear segments of the UFs. Both UFs use the same break points, which are the different levels of Rmin that are used in the simulations.

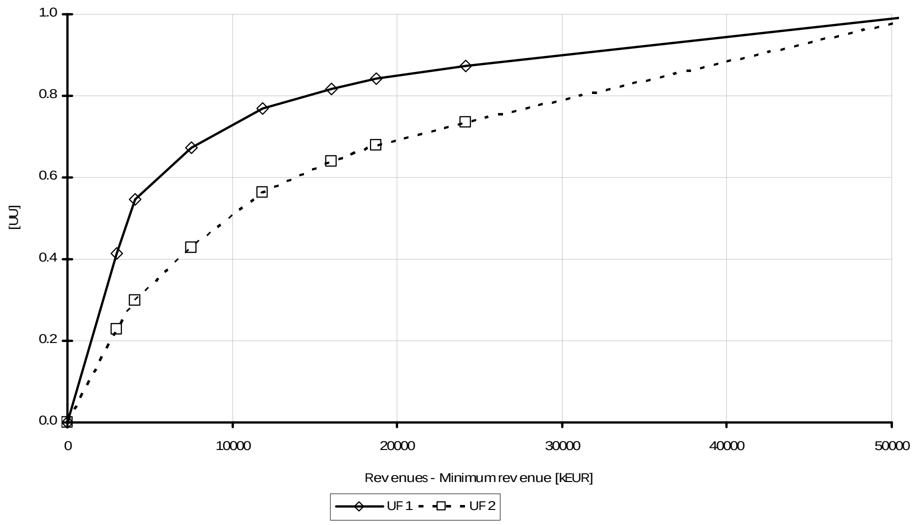

Fig 6: UF 1 and UF 2 expressed in accumulated yearly benefits (difference between scenario revenues and minimum scenario revenue).

We measure the risk aversion of Rmin constraint for the Utility Function indicator through the risk premium. The risk premium is the difference between the average revenue of all scenarios and the Certainty equivalent as defined in [11] of the scenario revenues utility. In Table X we can see the risk premiums for the different Rmin constraints. We can observe that the higher the required Rmin, the smaller the risk premium. For a risk premium equals to 0, the level of risk aversion is dictated by the UF. For 40% of Rmin and for the UF 2, the risk premium is negative. This indicates that the risk aversion is higher than the one sought by the company.

Table X – Utility Functions.

Rmin (kEUR)	**Rmin (%) of Rmax**	**Risk Premium UF 1 (-)**	**Risk Premium UF 2 (-)**
0	**0%**	34%	22%
48'917	**5%**	19%	14%
50'002	**10%**	18%	14%
53'388	**20%**	17%	13%
57'742	**30%**	9%	7%
61'922	**40%**	1%	-2%

7. CONCLUSIONS

As mentioned above, this paper presents the highlights of the work which was conducted inside a European company on a part of its hydroelectric assets, with a specific focus on risk management benchmarking. Specific indicators that characterize the generation and revenues risk as well as the sources of risk were investigated.

The state of the art methodology to analyze a hydro system in a medium-term perspective is based on the Stochastic Dual Dynamic Programming (SDDP) methodology, which is widely applied.

For the specific hydro system studied in this paper, a series of inherent characteristics were identified via the analysis. The combination of small reservoirs with large turbines offer a high intra-week, but a lower inter-week flexibility, which reduces the energy transport within periods of one week to one month. The volume risk (inflows) has a lower relative influence than the price risk on the total yearly revenues. From the medium term optimization benefit analysis we deduct that, although the system has a limited energy transport potential, revenues are significantly improved.

The analysis of the contracting decision required to satisfy the risk aversion of the company describes the limits of the system's hedging through the hedging cost and the sum of differences. Using as a measure an indicator of an integer nature such as VaR, we observe that Rmin does not efficiently act as a proxy. On the contrary, CVaR, which has a similar nature as Rmin, is represented by the latter more efficiently.

Finally, for the measure of the risk aversion using as indicator the Certainty Equivalent of a Utility Function, we can observe the gradual improvements for the tighter Rmin levels. However, the use of a single Rmin with one penalty coefficient to represent a company's risk aversion cannot express with the same detail the risk aversion changes represented by a piecewise linear UF with multiple break points and ARAC coefficients. This leads to the conclusion that, although for the 40% Rmin a risk premium of zero is achieved, the constant penalty coefficient that is used for all the inadequate revenue scenarios indicates that hedging can be made more efficiently. This reasoning derives from the fact that since all levels of revenues are penalized applying the same penalty coefficient for the Rmin level required, the difference of preference is not shown. Omitting the difference of preference between the different levels of revenues under Rmin we end up in a hedging policy that does not contain the variation of risk aversion that is expressed in the utility function as the revenues increase. A solution to that is proposed through a piecewise linear Rmin function with different penalty coefficients at each Rmin breakpoint which results however to a more laborious calibration process.

8. FURTHER DEVELPOMENTS

In the future we intend to analyze case studies for systems with a different topology having greater potential for transport of energy. In the case of a system with a greater storage capacity, we will analyze the use of quarterly and yearly contracts. In addition we would like to make comparative analyses between simulations, with yearly profit periods and with quarterly profit periods, and observe the efficiency of risk aversion constraints.

Concerning the financial indicators of VaR, CVaR and Utility Function, we intend to further explore their efficiency in hydroelectric optimization when implemented as constraints.

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